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Tales that cost: Folklore and bank loan spreads

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ABSTRACT

This paper investigates whether cultural narratives embedded in folklore influence the pricing of syndicated loans. We combine loan-level data for European companies with the cross-cultural dataset of oral traditions compiled by Michalopoulos and Xue (2021) to examine whether stories about risk-taking shape loan spreads. We find that the presence of challenge-related motifs in a lender's cultural background is associated with higher spreads. More specifically, tales that portray unsuccessful outcomes lead to significantly higher loan spreads, while those depicting successful risk-taking have no discernible effect. A greater prevalence of failure over success in challenge-related folklore robustly predicts higher spreads across specifications. These findings suggest that cultural beliefs about risk—transmitted through folklore—affect how lenders perceive borrower uncertainty. By shaping the soft information environment in which credit decisions are made, ancestral narratives continue to influence the terms of modern financial contracts.

1. Introduction

Loan spreads are key to understanding the cost of borrowing for firms and are central to corporate financing decisions. They reflect a comprehensive assessment by lenders of the risks associated with extending credit to a borrower. Beyond their role in revenue generation, loan spreads also help align profitability with internal risk models and regulatory requirements. A considerable body of literature has examined the determinants of loan spreads ranging from the legal framework and macroeconomic environment to borrower characteristics (Delis, Hasan, & Ongena, 2020; Hao, Nandy, & Roberts, 2012; Hasan, Hoi, Wu, & Zhang, 2014; Ivashina, 2009; Qian & Strahan, 2007). More recently, a new body of research has begun to explore the influence of deep-rooted cultural factors on financial decision-making. In line with this, a set of works has shown the role of trust (Alvarez-Botas & Gonzalez, 2021), language (Godlewski & Weill, 2021), and religion (Chen, Huang, Lobo, & Wang, 2016) in explaining loan spreads.

In this paper, we extend this line of inquiry by investigating how folklore, as a form of ancestral cultural expression, influences loan spreads across countries. We propose that folklore, particularly stories that emphasize risk and its consequences, continues to shape the behavior of banks. These stories embed values and attitudes that inform how individuals within a culture assess uncertainty, engage in competition, and evaluate success or failure. Building on the work of Michalopoulos and Xue (2021), who have shown that folklore shapes economic attitudes, we posit that these enduring cultural motifs influence the loan spread.

Our central hypothesis is that the way a culture narrates and interprets risk through folklore influences contemporary economic behavior, including how banks price credit risk. In particular, we posit that the cultural beliefs internalized by loan officers or embedded within lending institutions shape how credit risk is assessed and priced. This view is consistent with research on soft information in banking, which emphasizes the importance of subjective, non-verifiable inputs in credit assessment (Liberti & Petersen, 2011). It also aligns with behavioral finance theories showing that decision-makers tend to overweight negative signals—a pattern known as loss aversion (Tversky & Kahneman, 1991). In our framework, folklore operates as a cultural lens through which uncertainty is interpreted, shaping credit risk perceptions and ultimately loan spreads. In cultures where oral traditions depict risk-taking as heroic and successful, lenders may perceive borrowers from those societies as more reliable risk-takers. This may translate into more favorable loan conditions, including lower loan spreads. In contrast, when folklore predominantly portrays risk as leading to failure, this may enhance perceived borrower riskiness and justify higher loan spreads.

To develop this idea, we draw on the recent and innovative work of Michalopoulos and Xue (2021), who construct a cross-cultural dataset of

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oral traditions based on the compilations of anthropologist Yuri Berezkin (Berezkin, 2015). In their framework, a "motif" refers to a recurrent element—be it a plot, character, or symbolic image—found in the traditional stories of a cultural group. By classifying motifs along dimensions such as the presence and outcome of risk-taking behavior (e.g., success or failure following a challenge or competition), they derive quantifiable measures of cultural attitudes toward risk. Their work shows that such motifs predict differences in contemporary trust, gender attitudes, and willingness to take risks, including among second-generation immigrants, suggesting a persistent influence of these cultural narratives on behavior.

While Michalopoulos and Xue (2021) focus on broader economic outcomes such as entrepreneurship and innovation, we explore whether the cultural representation of risk in folklore affects how loan contracts are priced. Our focus on the loan spread is motivated by its interpretive richness: it reflects the lender's assessment of expected loss, borrower quality, and compensation for risk—all elements deeply tied to the perception and tolerance of risk. If folklore shapes how people internalize and respond to risk, then it is plausible that these beliefs find expression in the cost of credit.

We conduct a cross-country investigation on a large dataset of loans to European companies. We combine the folklore measures from Michalopoulos and Xue (2021) with loan-level data from Bloomberg, which includes detailed information on loan characteristics, as well as information on the borrowing firm and the lending bank. Importantly, we are able to link loans to cultural groups, which enables a micro-level analysis of the influence of folklore on loan spreads. We perform regressions to identify the effect of folklore on loan spreads, controlling for a rich set of loan, firm, bank, regional, and country characteristics.

European countries provide a particularly insightful context for analyzing the impact of folklore on loan spreads. This is due to a unique combination of cultural heterogeneity and a predominantly bank-oriented financial environment. Across Europe, there exists a remarkable diversity of folklore traditions, myths, and cultural narratives, often varying significantly even within national borders. At the same time, the European financial landscape is characterized by a strong reliance on bank-based financing. Unlike in more market-based systems, such as the United States, European firms rely heavily on bank credit as their primary source of external funding. This structural dependence on banks enhances the relevance of investigating loan pricing decisions, as it suggests that any cultural or folkloric influence on credit risk assessment is likely to have a tangible impact on the borrowing costs across the continent.

By way of preview, we uncover three main findings. First, stories that emphasize challenge and competition are associated with higher loan spreads, suggesting that such narratives elevate the perception of risk. Second, motifs involving unsuccessful outcomes in risk-taking scenarios are also associated with higher loan spreads. In contrast, stories portraying successful risk-taking have no significant effect on loan spreads. Third, a greater prevalence of failure over success in challenge-related tales corresponds to higher loan spreads. These results indicate that folklore influences loan pricing. Specifically, cultural narratives that frame risk-taking as more likely to result in failure appear to heighten perceived risk, thereby increasing the cost of borrowing. We further investigate how bank-level and firm-level heterogeneity can influence the findings. We tend to show that folklore seems to matter more for stronger banks and firms.

Our research contributes to two strands of the literature. First, we enrich the literature on the determinants of loan spreads. Beyond the well-documented role of legal institutions and borrower characteristics (Delis et al., 2020; Hasan et al., 2014; Ivashina, 2009; Qian & Strahan, 2007), we introduce folklore as a previously unrecognized explanatory variable. We therefore complement the recent literature devoted to cultural factors of loan spreads (Alvarez-Botas & Gonzalez, 2021; Chen et al., 2016; Godlewski & Weill, 2021). Second, we contribute to the nascent but promising literature on the economic impact of folklore. Michalopoulos and Xue (2021) provided pioneering evidence that motifs in oral traditions predict cross-country differences in entrepreneurship, innovation, and risk attitudes. We extend their analysis to the domain of financial contracts, moving from macro-level outcomes to the micro-level pricing of loans. Importantly, we shift the unit of observation from the country to the loan, and from aggregate outcomes to contract terms, thereby providing a new and granular perspective on the economic significance of folklore.

The rest of the paper is organized as follows. Section 2 discusses the background of the research question. Section 3 presents the data and empirical methodology. Section 4 reports the results. Section 5 displays the robustness checks. Section 6 concludes.

2. Background

2.1. Folklore and cultural narratives of risk

Michalopoulos and Xue (2021) draw on the work of anthropologist Yuri Berezkin, who cataloged myths and oral traditions worldwide to build a dataset suitable for quantitative analysis of folklore. Berezkin defines folklore as "all kinds of traditional stories and tales, long and short, sacred and profane" (2015, p.58), found in more than one cultural group. These stories are passed down vertically (across generations) or spread horizontally (through communication between groups).

To enable cross-cultural comparisons, Berezkin introduces "motifs"—recurring elements, episodes, or images found in at least two different traditions (2015, p.61). Folklore motifs often present starkly different narratives around the outcome of risk-taking. In one motif (K27g), the hero is ordered to bathe in boiling water but emerges unharmed, while the antagonist attempting the same task perishes—a story that celebrates resilience and hidden strength. By contrast, in another motif (K27l1), a character voluntarily freezes himself into the ice but becomes trapped, unable to escape—a sobering tale of overconfidence and irreversible failure. These contrasting narratives illustrate how cultures embed either encouragement or caution in the face of uncertainty, shaping whether risk-taking is viewed as valorous or perilous. His dataset covers 958 cultural societies from 199 countries, with 2564 motifs. The median motif appears in 18 traditions, and the median group contains 62 motifs. This allows researchers to quantify how often particular motifs appear in the stories of a group.

Despite being sourced mostly from early 20th century material, these motifs are believed to reflect enduring cultural values. Anthropology literature suggests that many oral traditions date back centuries or even millennia and carry deeply rooted values (Silva & Tehrani, 2016; Vansina, 1985). Michalopoulos and Xue (2021) further show that the influence of folklore on economic behavior persists even among second-generation immigrants, highlighting the deep-rooted and lasting nature of these cultural narratives.

Because oral traditions survive both time and migration, they are likely to reflect and help shape enduring group values. As Michalopoulos and Xue point out, "images and episodes in folklore appear to endure and possibly still shape how individuals perceive the world today" (2021, p.2041).

To study how folklore relates to contemporary cultural values, they classify motifs according to the features they are interested in: risk-taking, trust, and gender norms. They use ConceptNet, a semantic network, to identify motifs associated with certain themes. For risk-taking, the focus of our study, they consider two seed words by identifying motifs whose descriptions reflect situations of 'challenge' or 'competition,' using these as indicators of how different cultures perceive risk. Next, they validate ConceptNet's selections using human coders hired via Amazon Mechanical Turk. On average, nine workers rate each motif as depicting a successful, unsuccessful, or unclear outcome—or reject its link to challenge or competition. This approach provides data on the number and outcomes of risk-related motifs in each cultural group, allowing computation of the share of successful, unsuccessful, unclear, and unrelated (N/A) motifs. They also calculate a "Relatively unsuccessful" measure: the share of unsuccessful motifs minus successful and unclear motifs.

Finally, they investigate the relationship between these folklore variables and three country-level measures of risk-taking: the Global Preferences Survey (GPS) risk-taking score from Falk et al. (2018), new business registrations per capita, and patents per capita. They find evidence that a higher proportion of successful motifs is positively associated to a higher GPS score, while a greater value of the "Relatively unsuccessful" variable is negatively associated with new business registrations per capita and with patents per capita. In sum, Michalopoulos and Xue (2021) show that folklore content around risk-taking predicts modern economic behavior.

2.2. Soft information and behavioral perspectives on credit risk assessment

Folklore, as detailed in the preceding section, offers a window into how cultures encode perceptions of risk, reward, and uncertainty through oral narratives. These stories, passed down through generations, often reflect deeply rooted priors about the consequences of risk-taking—whether it is depicted as courageous and rewarded or reckless and punished. When internalized by economic agents, such cultural content can shape how individuals perceive and respond to risk in professional decision-making. In the context of banking, these ingrained priors may influence how lenders interpret borrower characteristics and assess credit risk, even in the presence of formal financial data. In this way, folklore can act as a subtle but persistent form of soft information—informally shaping the mental models and evaluative heuristics that credit officers bring to lending decisions.

When paired with well-documented behavioral biases such as loss aversion and negativity bias, these cultural priors can result in systematic distortions in credit risk perception. Psychological research has shown that individuals tend to overweight potential losses relative to gains (Tversky & Kahneman, 1991) and give greater attention to negative than to positive stimuli (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001). If loan officers operate in an environment where cultural narratives disproportionately depict failure in the face of risk, these tendencies may be reinforced and reflected in more conservative lending behavior. Consequently, similar borrowers may face different lending terms—such as higher spreads or tighter collateral requirements—depending on the cultural background of the lead lender.

Credit risk assessment is not a purely mechanical or data-driven process. It involves judgment, interpretation, and context-specific reasoning. In syndicated lending, where loans are often bespoke and involve complex borrowers or projects, the lead arranger plays a central role in setting terms and underwriting risk. This setting provides fertile ground for the influence of soft information—that is, qualitative inputs that are difficult to verify, communicate, or codify (Liberti & Petersen, 2011). Loan officers frequently rely on such inputs when hard signals—such as credit ratings, accounting quality, or financial ratios—are unavailable, noisy, or difficult to interpret. Prior research shows that soft information can significantly shape contract design, including loan maturity, spread, and covenant structures (Berg, Saunders, & Steffen, 2015; Bushman & Wittenberg-Moerman, 2012). In our context, we argue that culturally shaped beliefs, including those rooted in oral traditions, operate as a latent layer of soft information—shaping how risk is perceived, how borrower characteristics are evaluated, and ultimately how loan contracts are priced.

3. Data and methodology

3.1. Data

We extract from Bloomberg all loans to European borrowers with effective dates between January 1999 and December 2017. This provides information on loan facility amount, spread, maturity, covenants, collateral, date, type (revolver, term…), purpose (corporate, refinance, acquisition…), currency, etc. We exclude loans to firms from the financial industry and from the public sector.

We also extract data on the lenders, including their identity (name and ticker when available), nationality (country of incorporation), location (headquarters city), roles (or title), and number (within the banking pool). We identify the lead lender of each banking pool using the "Loan Agent" variable provided by Bloomberg. Lead lenders are the pivotal lenders in a syndicate because they establish relationships with borrowers, perform due diligence, negotiate contract terms and monitor borrowers (Bushman & Wittenberg-Moerman, 2012; Ross, 2010). We only keep loans for which all lender information is available, in particular a uniquely identified lead lender. Using borrower and lead lender identifiers we complete the sample with data from their respective financial statements where available (such as size, leverage, profitability, liquidity).[1]

We combine Bloomberg data with data on folklore from Michalopoulos and Xue (2021). We rely on lead lender headquarters city location with the closest cultural society using Berezkin (2015) coordinates of the centroids of each folklore group to compute a geographical distance. We assume that the cultural background of the lead lender is proxied by the location of its headquarters. This is motivated by the institutional role of lead arrangers, who structure the deal, underwrite the risk, and set the loan spread (Chaudhry & Kleimeier, 2015; Gopalan, Nanda, & Yerramilli, 2011). As these functions are generally centralized at the bank's headquarters, this location provides a reasonable anchor for attributing cultural characteristics. Hence, we take advantage of the subnational level granularity of the cultural data. Finally, we gather country-level data from various sources (World Bank, European Commission).[2]

3.2. Measuring folklore

We consider folklore by constructing six independent variables based on the classification introduced by Michalopoulos and Xue (2021). First, we consider *Challenge* indicating the total fraction of a culture's motifs related to challenge/competition terms. It is computed by dividing the number of challenge/competition related motifs by the total motif count for a given culture (Berezkin group). This variable serves as an overall measure of how extensively a folklore tradition addresses risk-taking, without distinguishing among outcomes. Second, we consider four variables which can be seen as components of *Challenge*: *Successful, Not successful, Unclear, N/A*. *Successful* and *Not successful* capture respectively the proportion of a culture's motifs depicting a character who, when faced with a challenging or competitive situation, ultimately achieves a positive or negative outcome, respectively. *Unclear* measures the share of motifs where the character's outcome cannot be definitively classified as either successful or unsuccessful. *N/A* denotes the fraction of motifs that automated semantic methods classify as related to risk-taking, but that human coders identify as unrelated according to Michalopoulos and Xue (2021). Finally, *Relatively Unsuccessful* is defined as (*Not successful* – *Successful*).[3] This measure provides insight into the relative prominence of negative outcomes compared to positive ones.

[1] We can pull this additional information for listed companies only, which reduces the sample size when including financial information.

[2] Definitions and sources of all variables are in Table A.1 in the appendix.

[3] Michalopoulos and Xue (2021) define a 'Relatively Unsuccessful' variable as the share of unsuccessful motifs minus the combined share of successful and unclear motifs. In contrast, we compute *Relatively Unsuccessful* as the difference between the shares of unsuccessful and successful motifs only, excluding unclear cases. This adapted definition sharpens the contrast between positive and negative outcomes, aligning more closely with our focus on risk asymmetry in credit pricing.

An important methodological choice is whose folklore to consider. In principle, both borrower and lender could come from different cultural backgrounds. However, in syndicated lending, the final loan terms emerge as an equilibrium between the borrower and a syndicate led by a (lead) bank, which structures the deal, assembles participants, and ultimately sets the spread (Chaudhry & Kleimeier, 2015; Gopalan et al., 2011; Ross, 2010). Although borrowers may hold bargaining power, it is the lead lender that underwrites risk and establishes the baseline spread (Dennis & Mullineaux, 2000; Gatti, Kleimeier, Megginson, & Steffanoni, 2013; Ivashina, 2009; Lee & Mullineaux, 2004; Sufi, 2007). Since the loans in our sample represent successfully concluded agreements (i.e. closed deals), we posit that pricing primarily reflects the lead lender's perception of credit risk—hence, its cultural and folklore-based attitudes toward risk-taking have a pivotal influence. Accordingly, we hypothesize that a lead lender's folklore-rooted views on challenge and competition shape credit risk assessments and, consequently, loan spreads.

3.3. Methodology

To conduct our empirical analysis, we perform OLS regressions with standard errors clustered at the lead lender folklore group level[4] and estimate the following model:

$$\text{Spread}_i = \alpha + \beta\ \text{Folklore}_j + \delta\ \text{Controls}_{i,j,k,l,m} + \varepsilon_i \tag{1}$$

where *i* indexes the loan, *j* the bank, *k* the firm, *l* the region, *m* the country, *Controls* is the set of control variables, and ε_i is the error term.

Our principal dependent variable is the loan-level spread, measured as the logarithm of the basis-point spread over a floating interbank benchmark rate (e.g., Libor). We focus on lead lender folklore group characteristics as the main explanatory variables. Specifically, we employ *Challenge*—or its component shares (*Successful, Not successful, Unclear, N/A*)—as well as *Relatively Unsuccessful*. This approach yields three primary specifications, each featuring a distinct set of folklore measures.

Following the extant literature, notably Bae and Goyal (2009), Giannetti and Yafeh (2012), Qian and Strahan (2007), we include a broad set of control variables at the loan, bank, firm, region, and country level. At the loan level, we account for maturity in years (*Maturity*), the presence of collateral (*Secured*), amount with the logarithm of millions of USD (*Amount*), the presence of financial covenants (*Covenants*), the syndicate size (*Lenders*), the reputation with an indicator for whether the lead lender is among the top three in the Bloomberg European league table (*League*), the lending relationship with a dummy variable whether the lead lender provided a loan to the same firm in the previous three years (*Relationship*). We also include a few variables not reported in the tables of estimations for space reasons: loan currency (euros or British pounds), type (term loan or not), purpose (acquisition, general corporate, LBO, project finance, debt refinancing) and year of origination dummies.

At the bank level, we control for bank size with the log of total assets (*Bank size*), profitability with the return on assets (*Bank ROA*), and capitalization with the ratio of equity to assets (*Bank capitalization*). At the firm level, we control for transparency with the rating from Moody's or S&P (*Firm rating*), size with the log of total assets (*Firm size*), leverage with the ratio of debt to equity (*Firm leverage*), profitability with the return on assets (*Firm ROA*), liquidity (*Firm current ratio*), and industry sector dummies. We winsorize all bank and firm-level variables symmetrically at the 5th percentile to deal with outliers.

At the country level, we control for banking development with the ratio of financial resources provided to the private sector by financial institutions divided by GDP (*Private credit*), stock market development with the total value of all listed shares in a stock market as a percentage of GDP (*Stock market*), the quality of institutions with the indicator *Rule of Law,* measuring the perceptions of the extent to which people have confidence in and abide by the rules of society, and the legal origin with dummies for *English legal origin* and for *German legal origin*. Finally, we incorporate one macroeconomic control at the region level for economic development with the logarithm of GDP per capita (*GDP* per capita).

[4] All estimation results are robust to using alternative clustering such as at the firm, bank, or country levels.

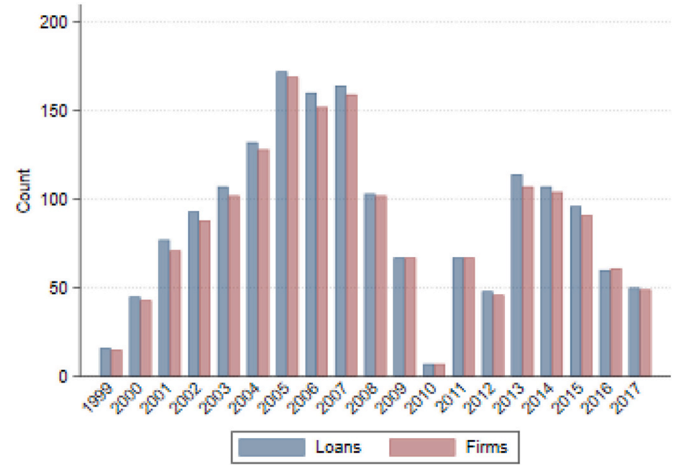

Fig. 1. Loans and firms by year.
This figure shows the evolution of the number of loans and firms by year.

Fig. 1 depicts the evolution of the number of loans and firms in our sample. It shows a pronounced cyclical pattern in loan activity and borrower presence, with the crisis period standing out as a clear inflection point, and a peak of about 175 loans and borrowers in 2005.

Table 1 shows the sample country composition. There are respectively 1671 unique loans to 1192 unique borrowing firms, provided by 316 lead banks. Among the 21 borrowing firms' countries in the sample, France, Germany, Italy, Netherlands, Spain account for 69% of the loans. Lead banks come from 23 different countries, including non-European countries such as Australia, Japan or United States, and they represent 33 unique Berezkin folklore groups.

Fig. 2 displays how challenge-related motifs are distributed across different Berezkin folklore groups (at the lead lender level). Each bar is divided into four segments—*Successful*, *Unsuccessful, Unclear,* and *N/A*—representing the average percentage of motifs that highlight challenging or competitive situations within a group's folklore. For instance, the percentage of motifs (among all motifs) related to challenge in the Wallon folklore group equals almost 10%, with the majority of motifs being related to success or unclear. Furthermore, we notice important variations: for example the Catawba group has nearly 15% of its motifs related to challenge, with a large proportion related to lack of success, while the Huron, Wyandot group has the lowest percentage of challenge-related motifs (below 5%) with an even split among success and unclear.

Table 2 provides descriptive statistics for all variables.[5] The average percentage of challenge related motifs in the sample is 5%, consistent with Fig. 2. The successful motifs are dominant (3.5%) and represent more than two times the unclear motifs (1.6%). The average loan spread equals 218 bps. Loans are large (2.21 billion $) with maturity above 6 years, frequently secured (43%) but rarely with covenants attached (9%). They are originated by syndicates of 12 lenders, where more than 1 out of 10 of the lead banks belongs to the league table and already had

[5] In addition, 77% of the loans are denominated in euros and 7% in British pounds, while 60% are term loans. Regarding their purpose, 15% support acquisitions, 16% general corporate needs, 22% leveraged buyouts (LBOs), 3% project finance, and 36% debt refinancing. With respect to industry sector, 25% of loans involve industrial firms, 23% consumer non-cyclical, 16% consumer cyclical, 12% communications, 8% basic materials, 6% utilities, and 5% energy.

Table 1
Country level composition.

Firm country	#Loans	#Firms	#Banks	Lender country	#Groups
Austria	8	7	5	Australia	1
Belgium	31	27	13	Austria	1
Czech Republic	5	4	5	Belgium	1
Denmark	10	8	4	Canada	1
Finland	36	23	10	Denmark	1
France	310	214	27	Finland	1
Germany	210	151	28	France	1
Greece	7	7	4	Germany	3
Hungary	3	3	2	Greece	1
Ireland	22	16	13	Ireland	1
Italy	145	107	23	Italy	4
Luxembourg	56	39	23	Japan	1
Netherlands	159	115	29	Netherlands	1
Norway	32	25	11	Norway	1
Poland	17	13	10	Poland	1
Portugal	14	8	8	Portugal	1
Slovenia	4	2	6	Slovenia	1
Spain	326	241	31	Spain	4
Sweden	68	43	14	Sweden	1
Switzerland	86	39	16	Switzerland	1
United Kingdom	122	100	34	Taiwan	1
				United Kingdom	1
				USA	3

This table displays the number of loans, firms, and banks (lead lenders) by (borrowing) firm country and the number of Berezkin folklore groups by (lead) lender country.

a lending relationship with the borrowing firm.

4. Results

4.1. Main estimations

We investigate whether folklore affects loan spread. We run regressions using the different folklore variables in Tables 3 to 5. In each table, we test three specifications of the set of control variables to check the sensitivity of our results to this choice. In column (1), we include loan controls, bank controls, and year dummies. In column (2), we add firm controls and industry dummies. In column (3), we add country dummies.

First, we consider only the *Challenge* variable, which is the share of all motifs related to challenge and competition, to analyze the effect of folklore. Table 3 reports these estimations. We find that *Challenge* is positive in all three specifications, being significant in the two last ones. Thus, we observe that loan spreads are higher when the lead lender is from a culture with a greater prevalence of stories related to challenge and competition. This suggests that merely referencing narratives involving risky endeavors—regardless of outcome—may elevate lenders' perception of uncertainty, thereby inducing higher spreads.

Second, we ask whether the impact of oral traditions on loan spreads depends on the outcomes portrayed in the tales. To this end, we consider the results for *Successful*, *Not successful*, *Unclear*, and *N/A*. As explained earlier, *Successful* and *Not successful* are respectively the shares of motifs dealing with challenge/competition in which a character has a positive or negative outcome, respectively. Table 4 reports these results.

We find that *Successful* is not significant in all estimations, suggesting that a higher share of motifs with a successful outcome does not affect loan spread. However, *Unsuccessful* is significantly positive in the two first specifications, being positive but not significant in the last specification. This finding provides some evidence that a higher share of motifs with an unsuccessful outcome would increase loan spread. It is consistent with the expectation that loan spread is higher when folklore portrays more frequently risk-taking as leading to failure. For the rest, *Unclear* and *N/A* are not significant in all estimations. These results suggest that folklore would affect loan spread mainly through the representation of unsuccessful outcomes in tales with challenge/competition. The asymmetry implies that lenders respond more strongly to cautionary tales than to heroic ones. This pattern aligns with behavioral insights from loss aversion theory, where individuals tend to overweight potential negative outcomes in decision-making under uncertainty (Tversky & Kahneman, 1991).

Third, we turn to the estimations with the single measure *Relatively unsuccessful*. This measure has the advantage of synthetizing the shares of successful and unsuccessful stories associated with challenge and competition. Table 5 displays the estimations. We find that *Relatively unsuccessful* is significantly positive in all estimations. We can therefore conclude that a higher relative share of motifs with failure outcome compared to motifs with success outcome in stories related to challenge/competition increases loan spread. This finding is consistent with the hypothesis that loan spreads are higher in cultures in which folklore predominantly portrays risk as leading to failure relative to leading to success.

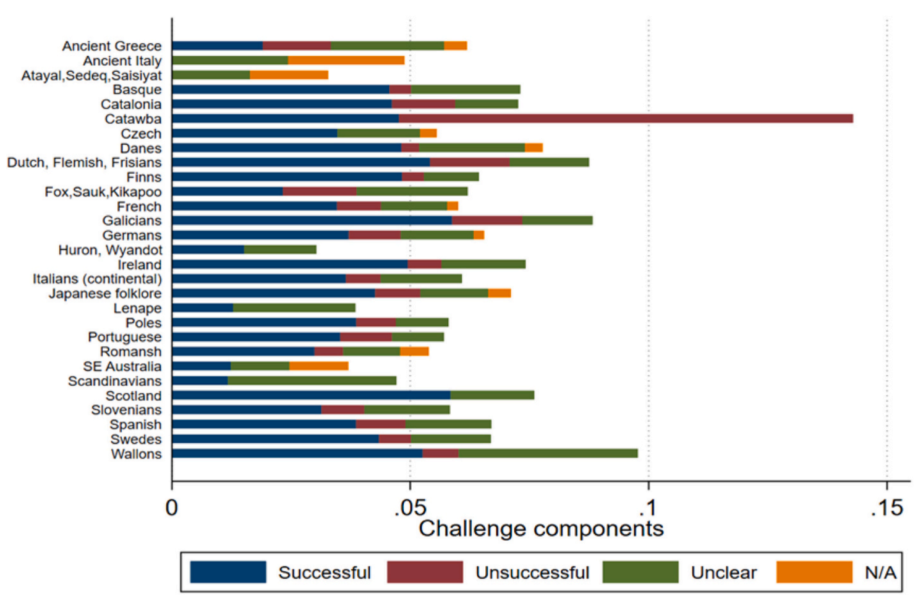

Fig. 2. Breakdown of challenge motifs by folklore group.
This figure shows the breakdown of the average % of challenge related motifs by Berezkin folklore group.

Table 2
Summary statistics.

Variable	Obs.	Mean	Std Dev.
Challenge	1671	0.0504	0.0147
Successful	1671	0.0353	0.0118
Not successful	1671	0.0094	0.0116
Unclear	1671	0.0164	0.0052
N/A	1671	0.0020	0.0026
Relatively unsuccessful	1671	−0.0259	0.0126
Loan spread	1671	218.0165	158.2520
Maturity	1671	6.1397	2.9860
Secured	1671	0.4320	0.4954
Amount	1671	2.21e+03	3.25e+04
Covenants	1671	0.0927	0.2900
Lenders	1378	12.4530	12.1594
League	1671	0.1241	0.3297
Relationship	1671	0.1137	0.3174
Bank size	1513	13.3224	1.4376
Bank ROA	1513	0.0048	0.0050
Bank capitalization	1513	0.0600	0.0471
Firm rating	1671	0.1398	0.3468
Firm size	888	6.6244	3.0817
Firm leverage	865	1.5011	1.7076
Firm ROA	835	0.0159	0.0432
Firm current ratio	873	0.0138	0.0066
GDP per capita	1634	10.6385	0.4694
Private credit	1556	104.2999	32.8124
Stock market	1519	80.9184	40.8276
Rule of law	1621	1.4259	0.4437
German legal origin	1671	0.2131	0.4096
English legal origin	1671	0.1043	0.3057
Corruption	1671	27.1853	4.6596
Uncertainty avoidance	1671	68.8227	17.9328
LT orientation	1671	58.9000	17.4690
Trust	1671	35.0548	12.5616
Christians	1671	69.1201	13.1491
Muslims	1671	4.4697	2.5826

This table reports the descriptive statistics for the variables employed in the analysis. All variables are defined in the Appendix.

The results are also economically significant. Based on the full specification in column (3), a one-standard-deviation increase in *Relatively unsuccessful* increases the loan spread by 22.86 basis points. Since the mean loan spread is 218.0165, this represents an increase of 10.5%.

Turning to controls, we find that loan controls are mostly significant and have signs in line with prior studies. Larger loans (*Amount*), loans with longer maturities (*Maturity*), secured loans (*Secured*), and loans with a higher number of lenders (*Lenders*) are associated with lower loan spreads. For bank controls, we show that more profitable banks (*Bank ROA*) and less capitalized banks (*Bank capitalization*) tend to charge higher loan spreads. Regarding firm controls, we observe as expected that larger firms (*Firm size*) and more profitable firms (*Firm ROA*) receive cheaper loans. Overall these results accord with those obtained in previous works explaining loan spread (Bae & Goyal, 2009; Godlewski & Weill, 2021).

To sum up, our results provide support for the effect of folklore on loan spread. A greater mention of challenge and competition in stories contributes to increase loan spread, suggesting that such narratives heighten perceived risk. When distinguishing between outcomes, motifs portraying unsuccessful outcomes are linked to higher loan spreads, while those with successful outcomes have no significant effect, indicating that tales emphasizing failed risk-taking drive up borrowing costs. Finally, a greater dominance of failure over success in challenge-related stories leads to higher loan spreads. Overall, our findings support the idea that folklore affects loan spreads, especially when cultural narratives depict risk-taking as more likely to end in failure. These results support the idea that cultural narratives portraying risk-taking as more likely to end in failure contribute to increasing loan spreads through greater perceived risk.

Table 3
Main estimations: loan spread and challenge.

	(1)	(2)	(3)
Challenge	2.396	7.114***	4.403**
	(1.522)	(1.678)	(2.093)
Amount	−0.068***	−0.056*	−0.083***
	(0.018)	(0.029)	(0.024)
Maturity	0.222***	0.189***	0.192***
	(0.049)	(0.063)	(0.053)
Secured	0.357***	0.315***	0.267**
	(0.046)	(0.089)	(0.102)
Covenants	0.060	0.045	0.004
	(0.113)	(0.103)	(0.088)
Lenders	−0.120**	−0.087*	−0.059
	(0.043)	(0.048)	(0.040)
League	0.016	0.046	0.039
	(0.044)	(0.050)	(0.039)
Relationship	−0.186**	−0.204**	−0.200**
	(0.069)	(0.096)	(0.094)
Bank size	0.033	0.018	0.032
	(0.028)	(0.038)	(0.030)
Bank ROA	−17.679**	−15.392**	−16.736**
	(6.440)	(6.931)	(7.579)
Bank capitalization	2.531***	2.082*	2.604**
	(0.872)	(1.044)	(1.116)
Firm rating		−0.009	−0.001
		(0.097)	(0.088)
Firm size		−0.029***	−0.027***
		(0.006)	(0.008)
Firm leverage		0.020	0.015
		(0.019)	(0.015)
Firm ROA		−0.028***	−0.027***
		(0.006)	(0.007)
Firm current ratio		−3.646	−4.140
		(3.065)	(2.560)
GDP per capita			0.098
			(0.106)
Private credit			0.003***
			(0.001)
Stock market			−0.004***
			(0.001)
Rule of law			0.131**
			(0.063)
German legal origin			−0.096
			(0.115)
English legal origin			0.325
			(0.310)
Intercept	4.385***	4.590***	3.852***
	(0.400)	(0.616)	(0.932)
Loan controls	Yes	Yes	Yes
Industry dummies	No	Yes	Yes
Year dummies	Yes	Yes	Yes
# loans	1248	574	538
# clusters	27	25	23
Adjusted R^2	0.53	0.58	0.61

This table displays the results of OLS regressions. The dependent variable is the log of *Loan spread*. All variables are defined in the Appendix. Loan controls include loan currency (EUR, GBP, USD), loan type (term, revolving), and loan purpose (acquisition, general corporate, LBO, project finance, debt refinancing). Standard errors are clustered at the (lead lender) Berezkin group level. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

4.2. *Additional estimations*

The results that we have reported so far show that folklore affects loan spread. However, one can question whether this effect is influenced by the financial characteristics of the lending bank or the borrowing firm.

First, we examine bank-level heterogeneity. Our main hypothesis here is that the positive effect of a higher share of motifs that associate risk-taking with failure relative to motifs that associate it with success on loan spread is stronger when the bank is more financially fragile. This is based on the idea that the perceived risk conveyed by folklore would be more influential when the risks for the bank are higher because of its

Table 4
Main estimations: loan spread and challenge components.

	(1)	(2)	(3)
Successful	−2.011	2.474	−3.294
	(4.006)	(3.347)	(3.634)
Not successful	3.312*	7.447**	7.303
	(1.834)	(3.240)	(4.656)
Unclear	−8.403	−6.248	−5.582
	(7.941)	(9.474)	(13.435)
N/A	3.674	11.722	12.752
	(10.432)	(22.554)	(31.092)
Amount	−0.066***	−0.054*	−0.086***
	(0.018)	(0.026)	(0.021)
Maturity	0.219***	0.181***	0.188***
	(0.049)	(0.058)	(0.051)
Secured	0.360***	0.323***	0.278***
	(0.044)	(0.082)	(0.095)
Covenants	0.067	0.044	0.017
	(0.114)	(0.102)	(0.086)
Lenders	−0.128***	−0.095*	−0.065
	(0.041)	(0.047)	(0.039)
League	0.004	0.003	0.028
	(0.043)	(0.036)	(0.042)
Relationship	−0.174**	−0.201**	−0.191**
	(0.064)	(0.096)	(0.091)
Bank size	0.022	0.027	0.009
	(0.031)	(0.034)	(0.043)
Bank ROA	−15.337**	−11.689	−15.406*
	(5.521)	(7.264)	(7.981)
Bank capitalization	2.403***	2.358**	2.244
	(0.852)	(1.032)	(1.426)
Firm rating		−0.007	0.009
		(0.097)	(0.084)
Firm size		−0.029***	−0.027***
		(0.007)	(0.009)
Firm leverage		0.021	0.016
		(0.018)	(0.015)
Firm ROA		−0.028***	−0.028***
		(0.007)	(0.007)
Firm current ratio		−3.686	−4.498
		(3.197)	(2.630)
GDP per capita			0.068
			(0.099)
Private credit			0.004***
			(0.001)
Stock market			−0.004***
			(0.001)
Rule of law			0.166**
			(0.063)
German legal origin			−0.127
			(0.124)
English legal origin			0.304
			(0.299)
Intercept	4.859***	4.848***	4.807***
	(0.620)	(0.641)	(0.946)
Loan controls	Yes	Yes	Yes
Industry dummies	No	Yes	Yes
Year dummies	Yes	Yes	Yes
# loans	1248	574	538
# clusters	27	25	23
Adjusted R^2	0.53	0.58	0.61

This table displays the results of OLS regressions. The dependent variable is the log of *Loan spread*. All variables are defined in the Appendix. Loan controls include loan currency (EUR, GBP, USD), loan type (term, revolving), and loan purpose (acquisition, general corporate, LBO, project finance, debt refinancing). Standard errors are clustered at the (lead lender) Berezkin group level. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

situation.

Alternatively, it can be argued that **more robust banks due to greater resources, better risk management, or a stronger reputation—are more likely to internalize or respond to cultural cues, including those embedded in folklore.** This perspective implies that the effect of folklore may be stronger if financial institutions have the cognitive and informational capacity to process such signals. In this view, stronger banks might price in folklore-based perceptions more actively.

Table 5
Main estimations: loan spread and challenge relatively unsuccessful.

	(1)	(2)	(3)
Relatively unsuccessful	4.304*	6.798**	7.914***
	(2.299)	(3.116)	(2.153)
Amount	−0.069***	−0.066**	−0.092***
	(0.018)	(0.028)	(0.025)
Maturity	0.222***	0.189***	0.190***
	(0.050)	(0.063)	(0.053)
Secured	0.360***	0.343***	0.287***
	(0.046)	(0.081)	(0.095)
Covenants	0.058	0.043	0.010
	(0.112)	(0.102)	(0.087)
Lenders	−0.123***	−0.076	−0.058
	(0.042)	(0.047)	(0.039)
League	0.030	0.057	0.061
	(0.044)	(0.053)	(0.042)
Relationship	−0.180**	−0.197**	−0.193**
	(0.066)	(0.093)	(0.091)
Bank size	0.005	−0.024	−0.020
	(0.036)	(0.055)	(0.041)
Bank ROA	−18.086***	−15.469**	−18.288**
	(6.343)	(7.479)	(7.330)
Bank capitalization	2.084*	1.666	1.685
	(1.025)	(1.504)	(1.396)
Firm rating		−0.002	0.016
		(0.099)	(0.085)
Firm size		−0.029***	−0.028***
		(0.006)	(0.008)
Firm leverage		0.016	0.013
		(0.017)	(0.015)
Firm ROA		−0.029***	−0.029***
		(0.006)	(0.007)
Firm current ratio		−4.188	−4.926*
		(2.979)	(2.564)
GDP per capita			0.101
			(0.109)
Private credit			0.004***
			(0.001)
Stock market			−0.005***
			(0.001)
Rule of law			0.158**
			(0.058)
German legal origin			−0.122
			(0.114)
English legal origin			0.294
			(0.305)
Intercept	4.972***	5.623***	4.962***
	(0.590)	(0.859)	(0.821)
Loan controls	Yes	Yes	Yes
Industry dummies	No	Yes	Yes
Year dummies	Yes	Yes	Yes
# loans	1248	574	538
# clusters	27	25	23
Adjusted R^2	0.53	0.58	0.61

This table displays the results of OLS regressions. The dependent variable is the log of *Loan spread*. All variables are defined in the Appendix. Loan controls include loan currency (EUR, GBP, USD), loan type (term, revolving), and loan purpose (acquisition, general corporate, LBO, project finance, debt refinancing). Standard errors are clustered at the (lead lender) Berezkin group level. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

We consider three bank-level variables: *Bank size*, *Bank ROA*, and *Bank leverage.* We test these hypotheses by considering subsamples based on the median of each bank-level variable. Table 6 reports the results. Panels A and B respectively display the results for observations above and below the medians. We again use the three specifications for folklore variables. Columns (1)–(3) consider *Challenge*, while Columns (4)–(6) use the combination of *Successful*, *Not successful*, *Unclear*, and *N/A*, and Columns (7)–(9) consider *Relatively unsuccessful.*

The findings reveal a nuanced picture. For the *Challenge* variable, we find it is significantly positive only for banks that are less profitable and

Table 6
Additional regressions on sub-samples based on bank variables medians.

Panel A: Above medians

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Bank size	Bank ROA	Bank equity to assets	Bank size	Bank ROA	Bank equity to assets	Bank size	Bank ROA	Bank equity to assets
Challenge	2.869	2.217	5.503***						
	(2.605)	(2.618)	(1.884)						
Successful				−10.971	−10.610	5.146			
				(7.749)	(6.805)	(4.588)			
Not successful				16.223**	16.004**	1.607			
				(5.747)	(5.951)	(5.261)			
Unclear				23.679	27.007	−16.122			
				(15.224)	(16.748)	(15.639)			
N/A				82.153*	96.093**	−13.204			
				(39.603)	(42.087)	(32.161)			
Relatively unsuccessful							9.342**	8.443**	6.061**
							(3.139)	(3.094)	(2.402)
Intercept	1.056	1.506	4.657**	1.007	3.412**	5.111**	2.741	3.225**	5.531***
	(2.456)	(1.481)	(1.669)	(1.800)	(1.298)	(1.984)	(1.956)	(1.381)	(1.544)
# loans	264	248	234	264	248	234	264	248	234
# clusters	11	19	21	11	19	21	11	19	21
Adjusted R^2	0.62	0.65	0.65	0.63	0.67	0.65	0.63	0.66	0.64

Panel B: Below medians

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Bank size	Bank ROA	Bank equity to assets	Bank size	Bank ROA	Bank equity to assets	Bank size	Bank ROA	Bank equity to assets
Challenge	4.996	9.044***	−10.726						
	(3.379)	(2.519)	(6.732)						
Successful				−0.596	9.103*	−28.737***			
				(7.218)	(4.708)	(6.478)			
Not successful				3.933	5.524	22.941**			
				(5.600)	(6.030)	(10.396)			
Unclear				−14.450	−11.002	31.633**			
				(10.995)	(8.346)	(12.396)			
N/A				−26.248	−26.295	8.770			
				(24.585)	(17.124)	(38.538)			
Relatively unsuccessful							5.436	1.697	22.307***
							(4.675)	(5.482)	(6.312)
Intercept	8.525***	5.219***	4.361***	9.065***	5.339***	4.440***	8.450***	5.452***	4.954***
	(0.765)	(1.493)	(0.979)	(1.020)	(1.652)	(0.959)	(1.116)	(1.757)	(0.886)
# loans	266	281	296	266	281	296	266	281	296
# clusters	23	18	13	23	18	13	23	18	13
Adjusted R^2	0.68	0.62	0.62	0.68	0.63	0.63	0.68	0.62	0.63

This table displays the results of OLS regressions. The dependent variable is the log of *Loan spread*. All variables are defined in the Appendix. All regressions include loan controls, industry and year dummies, and bank, firm, region, and country variables. Loan controls include loan currency (EUR, GBP, USD), loan type (term, revolving), and loan purpose (acquisition, general corporate, LBO, project finance, debt refinancing). Country level variables include *Private credit, Stock market, Rule of law, German legal origin, English legal origin*. Standard errors are clustered at the (lead lender) Berezkin group level. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

more capitalized. This suggests that more conservative financial institutions—such as those operating under tighter capital constraints or with low risk tolerance—may be especially influenced by culturally shaped perceptions of risk in their lending decisions.

When we consider the detailed components of folklore, *Not successful* is significantly associated with higher loan spreads in subsamples of the largest and most profitable banks, as well as the least capitalized ones. This challenges the initial hypothesis and supports the alternative view: more robust or better-performing banks may actively process and incorporate folklore-related cues, possibly as a form of soft information in credit risk evaluation.

Finally, using the *Relatively unsuccessful* measure, we observe a significant positive effect for the largest and most profitable banks, while it is consistently significantly positive across both subsamples for bank capitalization. This pattern suggests that even strong banks—those with greater information capacity and analytical resources—respond to the cultural framing of risk in folklore when pricing loans It suggests that the influence of folklore is not limited to situations of heightened vulnerability but may also play a role in shaping the decisions of powerful financial actors. Overall these findings tend to support the alternative hypothesis.

Second, we analyze firm-level heterogeneity. Specifically, we focus on three key indicators of firm financial health: *Firm size, Firm debt to equity,* and *Firm ROA*. Our core hypothesis is that financially fragile firms may be more affected by folklore that emphasizes the dangers and failures of risk-taking. The reasoning is that, when assessing firms already perceived as risky, lenders may be more sensitive to additional, culturally derived signals of risk, especially those embedded in narratives that portray risk-taking as likely to result in failure.

However, an alternative hypothesis merits consideration. It posits that folklore may matter more for financially stronger firms, such as large, profitable, and well-capitalized companies. In this view, lenders dealing with firms whose fundamentals do not raise immediate concerns may rely more on soft information—such as culturally shaped perceptions of risk—to fine-tune their credit assessments. Stronger firms may also operate in a more competitive lending environment, where pricing decisions reflect subtler factors beyond basic financial metrics. As such, folklore could exert a greater impact on loan spreads precisely where hard information offers less differentiation.

To test these competing views, we split the sample at the median of each firm-level variable and estimate regressions separately for firms above and below the threshold. Table 7 reports the results. Panel A presents the estimates for firms with characteristics above the median, and Panel B for firms with characteristics below the median. As before, we rely on three folklore specifications: Columns (1)–(3) use *Challenge*, Columns (4)–(6) decompose it into *Successful*, *Not successful*, *Unclear*, and *N/A*, while Columns (7)–(9) focus on *Relatively unsuccessful*.

The findings reveal a compelling pattern. For the *Challenge* variable, we observe significant positive effects only for the least profitable firms, indicating that the general emphasis on challenge and competition in folklore can amplify risk perception in firms whose profitability is already low.

More strikingly, when we consider the disaggregated folklore variables, we find that *Not successful* motifs are significantly associated with higher loan spreads only for firms that are larger, more profitable, and less indebted – firms that appear less risky. Finally, we similarly observe that *Relatively unsuccessful* is significantly positive for the largest, and the least indebted firms. It is also significantly positive for the least profitable firms.

Thus, these results tend to support the alternative hypothesis: the influence of folklore is more pronounced for stronger firms, possibly because their baseline financial metrics provide fewer warning signs, leaving more room for lenders to incorporate culturally shaped risk perceptions. In contrast, for weaker firms, loan spreads may be dominated by hard financial constraints, crowding out the influence of soft factors such as folklore.

Overall, our additional estimations indicate that the effect of folklore is not uniform across the financial spectrum. While one might expect financially fragile banks and firms to be more susceptible to folklore-driven perceptions of risk, we find that culturally rooted narratives also influence pricing decisions for stronger entities. In fact, banks with high profitability and size, and large or low-debt firms, appear especially sensitive to motifs portraying failed risk-taking. This may reflect a greater use of soft information in contexts where hard financial

Table 7
Additional regressions on sub-samples based on firm variables medians.

Panel A: Above medians

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Firm size	Firm debt to equity	Firm ROA	Firm size	Firm debt to equity	Firm ROA	Firm size	Firm debt to equity	Firm ROA
Challenge	2.801	2.199	2.509						
	(1.882)	(1.986)	(2.771)						
Successful				−10.659***	0.236	−4.160			
				(3.554)	(4.139)	(6.952)			
Not successful				11.984***	4.411	8.755*			
				(3.521)	(4.663)	(4.683)			
Unclear				10.351	−1.596	7.347			
				(10.089)	(11.406)	(14.219)			
N/A				29.268	−13.011	76.676**			
				(24.657)	(21.525)	(27.575)			
Relatively unsuccessful							9.192***	1.931	7.118
							(1.991)	(3.285)	(4.169)
Intercept	3.460	5.183***	2.169	5.015**	5.338***	3.248**	4.948**	5.488***	3.107*
	(2.249)	(0.785)	(1.554)	(2.357)	(0.873)	(1.365)	(2.236)	(0.869)	(1.500)
# loans	281	262	264	281	262	264	281	262	264
# clusters	17	22	20	17	22	20	17	22	20
Adjusted R^2	0.64	0.68	0.64	0.65	0.68	0.65	0.65	0.68	0.64

Panel B: Below medians

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Firm size	Firm debt to equity	Firm ROA	Firm size	Firm debt to equity	Firm ROA	Firm size	Firm debt to equity	Firm ROA
Challenge	4.482	4.680	6.707***						
	(2.702)	(3.174)	(2.075)						
Successful				−0.377	−6.988	0.206			
				(5.095)	(6.942)	(3.384)			
Not successful				4.811	11.137*	5.017			
				(5.386)	(5.652)	(3.453)			
Unclear				−6.860	5.945	−15.936			
				(14.501)	(14.159)	(13.904)			
N/A				1.925	95.588**	−60.377*			
				(29.264)	(34.441)	(29.261)			
Relatively unsuccessful							4.873	8.434**	7.542***
							(3.837)	(3.853)	(2.590)
Intercept	4.107***	3.565*	4.663***	4.696***	5.453***	5.403***	4.727***	4.924***	5.821***
	(0.889)	(1.707)	(0.924)	(1.013)	(1.504)	(0.945)	(1.017)	(1.482)	(1.017)
# loans	248	268	265	248	268	265	248	268	265
# clusters	22	18	19	22	18	19	22	18	19
Adjusted R^2	0.61	0.62	0.64	0.61	0.63	0.65	0.60	0.62	0.63

This table displays the results of OLS regressions. The dependent variable is the log of *Loan spread*. All variables are defined in the Appendix. All regressions include loan controls, industry and year dummies, and bank, firm, region, and country variables. Loan controls include loan currency (EUR, GBP, USD), loan type (term, revolving), and loan purpose (acquisition, general corporate, LBO, project finance, debt refinancing). Country level variables include *Private credit, Stock market, Rule of law, German legal origin, English legal origin*. Standard errors are clustered at the (lead lender) Berezkin group level. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

indicators are already strong. These results enrich our understanding of the folklore-loan spread relationship by showing that the economic impact of cultural narratives may depend on the ability of economic agents to process such information and integrate it into their pricing decisions.

5. Robustness checks

5.1. Controlling for culture

Folklore represents only one dimension of culture. As defined by Guiso, Sapienza, and Zingales (2006), culture encompasses the set of norms and beliefs that guide the behavior of the members of a social group and that are transmitted fairly unchanged from generation to generation. This broad definition includes elements such as religion, trust, and various other values. If folklore affects economic outcomes, it is plausible that other cultural components exert similar influences. Consequently, the observed effect of folklore on loan spreads may partly reflect the influence of these other cultural factors. To address this concern, we conduct additional estimations that control for alternative measures of culture, thereby isolating the specific role of folklore. Table 8 reports these results. In all estimations, we consider the broadest set of controls. We again rely on three folklore specifications: Columns (1)–(4) use *Challenge*, Columns (5)–(8) decompose it into *Successful*, *Not successful*, *Unclear*, and *N/A*, while Columns (9)–(12) focus on *Relatively unsuccessful*. We alternatively consider four sets of culture measures in the estimations.

First, we consider Hofstede culture dimensions. The six-dimensional framework developed by Hofstede (2001) has been widely used to analyze the impact of cultural characteristics. We focus on two dimensions that can affect the loan spread because they are related to risk perception (Aram & Nejadmalayeri, 2023; Zheng, El Ghoul, Guedhami, & Kwok, 2012): *Uncertainty avoidance,* which measures the tolerance of a society for uncertainty and ambiguity (a higher value indicates a lower tolerance for uncertainty and ambiguity); and *LT orientation*, which measures the extent to which a culture encourages delaying gratification. We add the two culture variables in columns (1), (5), and (9).

The results are very similar to those in the main estimations. We again observe significantly positive coefficients for *Challenge*, *Not successful*, and *Relatively unsuccessful*. Interestingly, we observe a significantly negative coefficient for *Successful*, implying that a higher share of challenge-related motifs leading to success leads to a lower loan spread. This additional result is therefore consistent with our interpretation of the results. We thus confirm our conclusion about the effect of folklore on loan spread.

Second, we take religion into account. Religion is a key component of culture that shapes the norms of societies (Iyer, 2016). For example, religious values have been shown to affect risk aversion (Hilary & Hui, 2009), firm cash holdings (Hu, Lian, & Zhou, 2019), and loan spread (Chen et al., 2016). We control for religion by including two religion measures at the country level: the percentage of Christians in the population (*Christians*), and the percentage of Muslims in the population (*Muslims*). Data come from the Pew Research Center. The religion variables are added in the estimations in columns (2), (6), and (10). We still observe our three key findings with the significantly positive coefficients for *Challenge*, *Not successful*, and *Relatively unsuccessful*.

Third, we include trust in the estimations. Prior literature emphasizes the influence of trust on financial outcomes such as loan decisions (Duarte, Siegel, & Young, 2012), or corporate cash holdings (Dudley &

Table 8
Robustness checks with country culture variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Challenge	4.294**	4.577**	4.481**	4.215*								
	(2.060)	(1.958)	(2.119)	(2.346)								
Successful					−9.224**	−4.390	−4.664	−4.014				
					(3.902)	(4.320)	(3.759)	(3.722)				
Not successful					9.178*	8.804*	7.892	7.931*				
					(4.449)	(4.914)	(4.794)	(4.601)				
Unclear					−4.997	−1.081	−6.726	−4.966				
					(12.401)	(13.802)	(14.425)	(12.949)				
N/A					−12.243	14.540	11.803	28.906				
					(29.309)	(28.579)	(30.605)	(34.533)				
Relatively unsuccessful									10.296***	8.710***	8.925***	8.361***
									(2.314)	(2.409)	(2.066)	(2.129)
Uncertainty avoidance	−0.001				−0.001				−0.001			
	(0.002)				(0.002)				(0.002)			
LT orientation	0.004*				0.007***				0.007***			
	(0.002)				(0.002)				(0.002)			
Christians		0.002				0.002				0.001		
		(0.002)				(0.002)				(0.002)		
Muslims		0.021*				0.019				0.027**		
		(0.012)				(0.016)				(0.012)		
Trust			0.003				0.005				0.005	
			(0.004)				(0.004)				(0.004)	
Corruption				0.018***				0.026***				0.021***
				(0.006)				(0.007)				(0.005)
Intercept	3.401***	3.533***	3.700***	3.209***	4.482***	4.570***	4.732***	4.021***	4.520***	4.755***	4.847***	4.276***
	(1.035)	(0.968)	(0.950)	(0.926)	(0.968)	(1.033)	(0.921)	(0.907)	(0.874)	(0.832)	(0.792)	(0.825)
# loans	529	529	529	529	529	529	529	529	529	529	529	529
# clusters	23	23	23	23	23	23	23	23	23	23	23	23
Adjusted R^2	0.61	0.61	0.61	0.61	0.62	0.61	0.61	0.62	0.62	0.61	0.61	0.61

This table displays the results of OLS regressions. The dependent variable is the log of *Loan spread*. All variables are defined in the Appendix. All regressions include loan controls, industry and year dummies, and bank, firm, region, and country variables. Loan controls include loan currency (EUR, GBP, USD), loan type (term, revolving), and loan purpose (acquisition, general corporate, LBO, project finance, debt refinancing). Country level variables include *Private credit, Stock market, Rule of law, German legal origin, English legal origin.* Standard errors are clustered at the (lead lender) Berezkin group level. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Zhang, 2016). Related to our work, Alvarez-Botas and Gonzalez (2021) investigate the effect of trust on loan spread. While no effect of trust on loan spread is found, they show that trust reduces loan spread when formal institutions are weak in one country, suggesting the existence of a substitution between formal institutions and trust to decrease loan rates.

We measure trust with the percentage of respondents who answer "Most people can be trusted" when asked "Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?" (*Trust*) from the World Values Survey. We add trust to the estimations in columns (3), (7), and (11). We again observe the significantly positive coefficients for *Challenge* and for *Relatively unsuccessful*. The coefficient for *Not successful* is still positive but not significant.

Fourth, we include corruption in the estimations. We follow the literature supporting the potential impact of corruption on financial decisions (e.g., Liu, 2016, for opportunistic behavior; Hossain, Hossain, & Kryzanowski, 2021, for corporate payouts). In particular, Bae and Goyal (2009) and Hossain, Kryzanowski, and Mia (2020) have found evidence that greater corruption increases the cost of bank loans. We measure corruption with the corruption perception index (*Corruption*) from Transparency International, where higher values indicate less corruption. This variable is added in the estimations in columns (4), (8), and (12). We again find that the coefficients for coefficients for *Challenge*, *Not successful*, and *Relatively unsuccessful* are significantly positive.

In summary, we find that the influence of folklore on loan spreads is still observed, even when we include alternative culture measures. Our findings that a greater mention of challenge and competition in stories, a larger share of motifs portraying unsuccessful outcomes, and a higher dominance of failure over success in challenge-related stories contribute to increase loan spread, are all preserved.

5.2. Endogeneity

To address potential endogeneity, we adopt a spatial instrumental-variable approach inspired by Marigo and Weill (2025). The idea is that the folklore of geographically neighboring cultural groups reflects long-term cultural diffusion but is exogenous to current financial decisions. We construct an instrument equal to the average difference between the shares of unsuccessful and successful challenge motifs among all Berezkin groups located within a 225 km radius around each lender's cultural area. This radius ensures sufficient coverage (each lender group has at least one cultural neighbor) while maintaining local cultural relevance. Smaller radii yield near-identical folklore values (producing collinearity), whereas broader thresholds introduce excessive regional overlap. The resulting "neighboring folklore" variable (*Relatively unsuccessful IV*) therefore captures exogenous spatial variation in folklore, independent of lenders' own narratives.

We focus on the specification considering the synthetic measure of folklore *Relatively unsuccessful*. Table 9 reports the results. The first-stage regression confirms a very strong correlation between a lender's folklore index and that of its neighbors: the estimated coefficient is 0.978 with a Wald F-statistic exceeding 800, indicating that the instrument is highly relevant. In the second-stage regression, the instrumented folklore variable remains positive and statistically significant at the 1% level, with an estimated coefficient of approximately 5.8. Lenders originating from culturally more "unsuccessful" regions—where folklore emphasizes failed over successful challenges—charge higher loan spreads, consistent with stronger risk aversion in pricing. Overall, the 225 km instrument validates the causal interpretation of our main result: cultural attitudes toward failure, embedded in regional folklore, shape banks' credit-pricing behavior through persistent, historically transmitted beliefs about risk and success.

5.3. Additional robustness checks

To ensure that the relation between folklore and loan pricing is not driven by unobserved heterogeneity at the country or industry level, we estimate several alternative specifications with increasingly demanding fixed effects (Table 10). We focus again on the specification considering the synthetic measure of folklore *Relatively unsuccessful.* In addition to the baseline year and industry fixed effects, we introduce lender country fixed effects, borrower country fixed effects, borrowing country × year fixed effects, and lender country × year fixed effects. These controls account for any time-varying macroeconomic or institutional factors affecting all banks within a country, as well as sectoral shocks that could simultaneously influence both lending conditions and borrowers' financial structure. Across all specifications, the coefficient on *Relatively Unsuccessful* remains positive and statistically significant, while the adjusted R^2 increases from approximately 0.63 to 0.75 as additional fixed effects are included. The persistence of the folklore coefficient confirms that the results are not driven by country-level business cycles, changes in national credit conditions, or sector-specific fluctuations. This evidence confirms the finding that folklore affects loan pricing.

We further check that the folklore effect is not confounded by systematic differences in regional development or socio-economic structure. To this end, we augment our baseline model with additional regional controls derived from the ARDECO (Annual Regional Database of the European Commission). Specifically, we match each borrowing firm's NUTS-2 region and year to (i) real GDP per capita, (ii) the share of population aged 25–64 with tertiary education (ISCED 2011 levels 5–8), and (iii) the logarithm of population density, computed from average annual population and regional area. These variables capture regional economic development, human capital, and urbanization. Table 11 reports these results. We consider three specifications. In all specifications, we include regional GDP per capita. We then alternatively test the addition of regional population density in column (1), regional average education in column (2), and both variables in column (3). The inclusion of these controls leaves the folklore coefficient virtually unchanged in magnitude and significance. The stability of the results indicates that the folklore–spread relationship is not driven by unobserved regional disparities in economic development, education, or population density.

Table 9
Instrumental variables.

	1st stage	2nd stage
	Relatively unsuccessful	Loan spread
Relatively unsuccessful IV	0.978***	
	(0.035)	
Relatively unsuccessful		5.808***
		(2.165)
#loans	538	538
#clusters	23	23
F	803.49	

This table displays the results of IV/2SLS regressions. In 1st stage, the dependent variable is *Relatively unsuccessful*. In 2nd stage the dependent variable is the log of *Loan spread.* The instrument is the *Relatively unsuccessful* variable constructed using data from the neighboring folklores in a radius of 225 km. F-statistic tests instrument relevance. All variables are defined in the Appendix. All regressions include loan controls, industry and year dummies, and bank, firm, region, and country variables. Loan controls include loan currency (EUR, GBP, USD), loan type (term, revolving), and loan purpose (acquisition, general corporate, LBO, project finance, debt refinancing). Country level variables include *Private credit, Stock market, Rule of law, German legal origin, English legal origin*. Standard errors are clustered at the (lead lender) Berezkin group level. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

6. Conclusion

In this paper, we examine whether and how folklore influences the pricing of syndicated loans. Our central premise is that oral traditions, through their depiction of risk-taking and its consequences, embed cultural attitudes that persist over time and continue to shape

Table 10
Robustness checks using various combinations of fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)
Relatively unsuccessful	7.151***	10.788***	10.977***	9.393***	12.368***	16.146***
	(1.794)	(1.759)	(1.480)	(2.960)	(2.770)	(3.080)
Year	Yes	Yes	Yes	No	No	No
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Borrower country	Yes	No	Yes	No	No	No
Lender country	No	Yes	Yes	No	No	No
Borrower country × Year	No	No	No	Yes	No	Yes
Lender country × Year	No	No	No	No	Yes	Yes
#loans	537	534	534	527	526	520
#clusters	23	20	20	22	20	20
Adj.R2	0.63	0.63	0.65	0.69	0.68	0.75

This table displays the results of OLS regressions. The dependent variable is the log of *Loan spread*. Various combinations of fixed effects are tested. All variables are defined in the Appendix. All regressions include loan controls, and bank, firm, region, and country variables. Loan controls include loan currency (EUR, GBP, USD), loan type (term, revolving), and loan purpose (acquisition, general corporate, LBO, project finance, debt refinancing). Country level variables include *Private credit, Stock market, Rule of law, German legal origin, English legal origin*. Standard errors are clustered at the (lead lender) Berezkin group level. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11
Robustness checks with additional regional variables.

	Addition of population density	Addition of tertiary education	Addition of population density and tertiary education
Relatively unsuccessful	8.990***	6.197***	7.211***
	(2.335)	(1.910)	(1.918)
#loans	484	499	469
#clusters	20	23	20
Adj.R2	0.64	0.64	0.65

This table displays the results of OLS regressions. The dependent variable is the log of *Loan spread*. Additional regional variables (referenced in the first row) are included. All variables are defined in the Appendix. All regressions include loan controls, industry and year dummies, and bank, firm, region, and country variables. Loan controls include loan currency (EUR, GBP, USD), loan type (term, revolving), and loan purpose (acquisition, general corporate, LBO, project finance, debt refinancing). Country level variables include *Private credit, Stock market, Rule of law, German legal origin, English legal origin*. Standard errors are clustered at the (lead lender) Berezkin group level. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

contemporary economic behavior. Specifically, we investigate whether the way risk is portrayed in folklore—through stories of success or failure—affects how banks perceive credit risk and, in turn, how they set loan spreads.

Our empirical analysis, based on a rich dataset combining folklore motifs and detailed loan characteristics for European borrowers, confirms that cultural narratives can have tangible financial consequences. The presence of motifs involving risk-taking is associated with higher loan spreads, suggesting that such stories elevate the perceived uncertainty of credit, regardless of outcome. However, distinguishing between outcomes reveals a deeper asymmetry: motifs depicting failure lead to significantly higher loan spreads, while those portraying success have no significant effect. This pattern is consistent with behavioral finance research emphasizing loss aversion and the disproportionate weight given to negative signals. A synthetic folklore variable—capturing the excess of failure over success in challenge-related stories—emerges as a robust predictor of loan spreads across all specifications.

Additional estimations shed light on the contexts in which folklore matters most. On the bank side, we find that stronger lenders are more sensitive to folklore-based cues, suggesting that the integration of cultural priors may be a deliberate and sophisticated form of soft information processing. On the borrower side, folklore effects are more pronounced for financially sound firms, where hard risk indicators are unlikely to trigger concern. In these settings, cultural narratives act not as substitutes for hard data, but as complementary heuristics that subtly influence credit assessments.

The implications are twofold. For international lenders and risk managers, awareness of the cultural scripts embedded in oral traditions can help explain cross-border variation in loan spreads not captured by standard risk models. For policymakers, our findings suggest that culture-sensitive risk assessment frameworks may be warranted, especially in multicultural lending contexts.

To conclude, this paper sheds light on the enduring influence of folklore in the realm of finance. The tales we tell—and those we inherit—carry with them encoded understandings of risk, reward, and failure. Far from being relics of the past, these narratives continue to shape the heuristics of decision-makers and the functioning of financial markets. In an age increasingly dominated by quantitative models and machine learning, our findings offer a timely reminder: not all data are digital, and not all signals are numerical. Sometimes, the stories of old still shape the price of risk—and the cost of capital.

Appendix A. Appendix

Definitions and sources of variables.

Variable	Definition and source
Folklore variables	
Challenge	Share (%) of motifs that depict a challenge-related motif. Source: Berezkin (2015).
Successful	Share (%) of motifs that depict a successful outcome. Source: Berezkin (2015).
Not successful	Share (%) of motifs that depict an unsuccessful outcome. Source: Berezkin (2015).
Unclear	Share (%) of motifs for which the outcome is unclear. Source: Berezkin (2015).

(*continued on next page*)

(*continued*)

Variable	Definition and source
N/A	Share (%) of motifs for which it is uncertain whether they depict a challenge related motif. Source: Berezkin (2015).
Relatively unsuccessful	Relative unsuccessfulness (%), computed as the difference between Not successful and Successful. Source: Berezkin (2015).
Loan variables	
Loan spread	Loan spread in basis points. Source: Bloomberg.
Maturity	Maturity of the loan in years. Source: Bloomberg.
Secured	=1 if the loan is secured by collateral, =0 otherwise. Source: Bloomberg.
Amount	Loan amount (in millions of USD). Source: Bloomberg.
Lenders	Number of lenders in the banking pool. Source: Bloomberg.
League	=1 if the lead lender of the banking pool is listed among the top 3 of the Bloomberg European league table, =0 otherwise. Source: Bloomberg.
Relationship	=1 if the lead lender of the banking pool issued a loan for the same borrowing firm during the last 3 years, =0 otherwise. Source: Bloomberg.
Bank variables	
Bank size	Logarithm of the lead lender total assets. Source: Bloomberg.
Bank capitalization	Lead lender equity to assets. Source: Bloomberg.
Bank ROA	Lead lender return on assets. Source: Bloomberg.
Firm variables	
Firm rating	=1 if the borrowing firm has a rating from Moody's or S&P (Senior Unsecured Debt or LT Issuer Credit), =0 otherwise. Source: Bloomberg.
Firm size	Logarithm of the borrowing firm total assets.
Firm leverage	Borrowing firm debt to equity.
Firm ROA	Borrowing firm return on assets.
Firm current ratio	Borrowing firm current assets to current liabilities.
Regional variables	
GDP per capita	Logarithm of the GDP per capita at the regional level (NUTS 2). Source: ARDECO (European Commission)
Country variables	
Private credit	Financial resources provided to the private sector by domestic money banks as a share of GDP. Source: Global Financial Development Database (World Bank).
Stock market	Total value of all listed shares in a stock market as a percentage of GDP. Source: Global Financial Development Database (World Bank).
Rule of law	Index indicating the perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. Source: World Governance Indicators (World Bank).
German legal origin	Dummy = 1, if the legal origin of the country is German, =0 otherwise. Source: La Porta et al. (2008).
English legal origin	Dummy = 1, if the legal origin of the country is English, =0 otherwise. Source: La Porta et al. (2008).
Corruption	Corruption perception index. Source: Transparency International.
Uncertainty avoidance	Index considering how unknown situations, uncertainty, and unexpected events are dealt with (e.g. a high uncertainty avoidance index indicates a low tolerance for uncertainty, ambiguity, and risk-taking). Source: Hofstede's website.
LT orientation	Index referring to the degree to which cultures encourage delaying gratification (e.g. long-term orientation emphasizes traits such as persistence, perseverance, thrift, saving, long-term growth, and the capacity for adaptation). Source: Hofstede's website.
Trust	Percentage of respondents replying “Most people can be trusted” when asked “Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?”. Source: World Values Survey - Integrated Values Surveys (2022) – Our World in Data.
Christians	Percentage of Christians. Source: Pew Research Center.
Muslims	Percentage of Muslims. Source: Pew Research Center.

Data availability

The authors do not have permission to share data.

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